Research on Tomato Nitrogen Content Nondestructive Testing Method Based on Multidimensional Image Processing Technology

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Abstract

This paper is aimed at greenhouse tomato nitrogen detection using hyperspectral imaging combined with three dimensional laser scanning technology. This technology extracts the nitrogen hyperspectral feature image and the plant three dimensional morphological characters, to achieve the rapid quantitative analysis of nitrogen in tomato. The characteristic spectrum of nitrogen was extracted, and the mean intensity characteristic of the image feature was obtained. Then based on the acquisition of the tomato hyperspectral image data cube at different nitrogen levels, the sensitive region stepwise regression combined with correlation analysis was performed. Based on the acquired three dimensional laser scanning data of tomatoes, the stem diameter, the plant height and other biomass characteristics of different nitrogen levels were obtained by establishing the spatial geometric model of tomato three dimensional point cloud. A multi-feature fusion model for tomato nitrogen detection was established by partial least square regression. The results showed that the R^2 in the constructed model was 0.94, with the accuracy significantly better than that of the single feature model established by using hyperspectral image and three dimensional laser scanning.

Keywords: Tomato, Nitrogen, Hyperspectral Image, 3D Morphological, Multi-Feature Fusion

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INTRODUCTION

Currently, the cultivated agriculture land area in China has already been 3.8 million hectares, among which the tomato planting area is 1.86 million hectares, and the production has reached nearly a third of the world output [1]. As a result, tomato is regarded as an extremely important vegetable crop. Globally, the most limiting crop growth factor is nitrogen (N) availability [2]. In addition, the demand for tomato by the growing population requires increase in the resource use efficiency of N for the crop [3]. However, lack of advanced scientific nutrition regulation and control method, the nitrogen fertilizer use efficiency of greenhouse tomato is only 35% less than a half of the developed countries [4, 5]. Nitrogen (N) fertilizer is an important component in plant interaction because it is part of the chlorophyll molecule, which gives the green color to the plants [6, 7]. In tomato production it has significant effect on the yield and quality [6]. Furthermore, it affects the tomato content of substances soluble in juice [8]. Besides, a good crop N nutritional status enhances drought tolerance of the crop [9]. Therefore, it is of practical significance to accurately monitor the information of tomato growth process and realize the precise control which is based on the requirements feedback of crop growth.

There are already many research achievements about the hyperspectral remote sensing, visual image and other crop nitrogen non-destructive testing method. These techniques have successfully replaced the traditional manual and chemical assay, because of the advantages of being rapid, timeliness with no influence on the crop growth [10-13]. But most of the studies only focused on the nitrogen nutrition diagnosis of the reflection characteristics differences which is led by the nitrogen enrichment and the paucity. The different nitrogen quantity will directly lead to diversity of the biomass, stem diameter and plant height. Therefore, such parameters can also be used as an effective feature for the inversion of crop nitrogen. Compared with the traditional visual image and the contact measurement method, 3D laser scanning can simultaneously obtain the overall morphology of the plant. In addition, the accuracy is also higher. The technology can further realize accurate extraction and analysis of integrated crop growth characteristics. In this study, the idea of combining hyperspectral imaging and 3D laser scanning technology was put forward. The tomato leaf scale hyperspectral image features, which were led by the nitrogen enrichment and the paucity, and the canopy scale biomass, plant height, stem diameter, morphological characteristics and differences would be fully utilized. Through the use of multi-scale and multi-feature information fusion in quantitative analysis of nitrogen in tomato, the detection accuracy of tomato nitrogen nutrition were effectively improved, to provide a scientific basis for the precise management of the water and fertilizer facilities.

MATERIALS AND METHODS

Samples Cultivation

The experiment was carried out in the Jiangsu University Provincial Key Laboratory of Modern Agricultural Equipment and Technology from September 2014 to December 2014. In order to realize the precise control of nitrogen in tomato, non-soil culture was used. Under the condition of ensuring the balance of other nutrient elements, the control of nitrogen was carried out to obtain the tomato samples with different nitrogen levels.

The test variety was Tomato Co 903. Nutrient solution according to Yamazaki formula[14], the samples was divided to 5 groups with different nitrogen treatment: N1, N2, N3, N4 and N5. The concentration (mass fraction) of N in the formula was 0%, 50%, 100%, 150% and 200% respectively. There were 10 plants for each treatment, with the total of 50 plants.

Experimental Methods

Multi-spectral images acquisition and transaction

The hyperspectral image data acquisition system was used to capture hyperspectral image data of tomato leaves[15], with the exposure time being 900 ms, and the scanning speed 1.25 mm/s, which ensured the image's clarity and non distortion. Then, Black and White field calibrations were conducted, with the intensity range set in 0--4000. The hyperspectral image data acquisition is based on Cube Spectral software platform. The spectral data sampled in 390.8 ~ 1050.1 nm, with a resolution of 1.3 nm synchronously acquire the high spectral image data cube composed of 512 different spectral bands in the sampling interval. The Data was processed using ENVI V4.0 software platform.

Tomato growth information scan and data acquisition

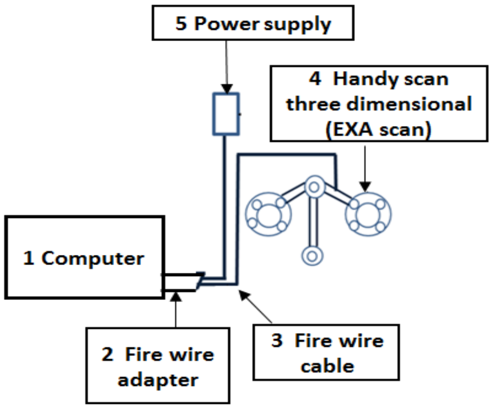


Figure 1. The 3D laser scanner which is composed of computer, Handy scan 3D (EXA scan), FireWire adapter, FireWire cable, power supply and other components.

The three-dimensional shape of tomato was obtained using the handheld self positioning 3D laser scanner. As shown in Figure 1, the 3D laser scanner is composed of computer, Handyscan3D (EXA scan), FireWire adapter, FireWire cable, power supply and other components. This instrument works at a speed of 25 measurements per second, with the resolution of 0.05 mm, the precision of 0.04 mm and the shooting range of 300 mm. It's field depth of vision is ±150 mm, and the laser cross region is 210 mm ×210 mm.

When scanning, first of all, the reflection target points with the diameter of 6 mm should be pasted on the tomato and the pot. The shape of the tomato plant is complex, so that every two adjacent points should be controlled at a distance no more than 20 mm. Then, the calibration board was measured with a three dimensional laser scanner to calibrate the sensor parameters. In order to ensure the clarity of the 3D shape model, it was set, by test analysis, as follows: the laser power was 65%, the shutter time was 7.2 ms, the resolution was 0.5 mm. One by one, the three dimensional data of all the tomato samples would be obtained through the handheld scanning method.

Plant nitrogen determination

The samples were determined by using the method of determination of nitrogen content and analyzed by AutoAnalyzer3 (AA3) continuous flow analyzer. The nitrogen content would be calculated by formula (1)[16].

$$N = \frac{c}{m \times (1 - w)} \times 100\% \qquad (1)$$

where, N stands for nitrogen content (%) of the test samples; c for the sample liquid instrument observation (mg); m for the weight of the test sample (mg); w for water content (%) of the test samples.

RESULTS AND ANALYSIS

Hyperspectral image feature extraction and analysis of tomato nitrogen

Image background segmentation

ENVI software was used in this study in order to obtain tomato leaf hyperspectral images, through the analysis of the threshold of the target image and background. Finally the 476 nm image was chosen based on the bimodal method to finish the threshold segmentation, with the threshold of 187. The binary target image is inverted by gray scale inversion after segmentation and filled the residual to remove isolated noise. On this basis, the original image pixels are multiplied with those of the binary target image, the hyperspectral image sequences of tomato sample could be obtained

Nitrogen characteristic spectrum extraction

In order to reduce the redundancy and improve the efficiency of the feature, the sensitive interval stepwise regression method[17] was used to select the characteristics of nitrogen. Previous studies showed that the tomato nitrogen sensitive range is mainly at the 390 ~ 471 nm, the 520 ~ 581 nm and the 610 ~ 673 nm spectral region[18]. The stepwise regression is a method that chooses variables based on their effect on the significant degree of nitrogen content.

The stepwise regression criterion adopted in this study is that the entered variable should be retained when condition of F > 3.10 established, it should be excluded when condition of F < 1.80 established. The relation expression of R2 > 0.5 should be ensured, and the number of variables in each group is not more than 4. According to the regulation, the regression equation of each interval is obtained as:

$$N_{390\sim471nm} = 0.98 + 4.03AG_{407} + 17.31AG_{422} - 6.38AG_{446} + 27.64AG_{454} \quad (2)$$

$$N_{520\sim581nm} = 1.56 - 6.53AG_{527} + 12.21AG_{549} + 9.36AG_{556} + 5.63AG_{578} \quad (3)$$

$$N_{610\sim673nm} = 1.29 + 31.56AG_{615} - 8.77AG_{643} + 5.41AG_{663} \quad (4)$$

Type: AGi (interval i: 390 ~ 700 nm) for hyperspectral image gray-scale variables; Nj (interval j: 390 ~ 471 nm, 520 ~ 581 nm, 610 ~ 673 nm) for nitrogen content in high sensitive spectral interval j predictive value.

On this basis, through the correlation analysis, finally the gray mean of the 454, 549, 556 and 663 nm image were selected as the nitrogen hyperspectral image characteristics.

Nitrogen characteristics expression and quantification

Figure 2 shows the tomato leaves characteristic image at 549 nm wavelength for four different nitrogen levels. It can be seen that the gradient of gray level is more obvious with the increase of nitrogen level. At specific wavelengths, the average gray level of the image can be used to represent the distribution of reflection intensity in the tomato sample region. The algorithm of the mean value of the gray scale is as follows:

$$AG = \frac{1}{N}\sum_{i=1}^{N} f_i(x, y) \quad (5)$$

Type: AG represents the tomato leaf image gray level at the sensitive wavelength, and N represents the number of pixels in the whole image (i=1,2,…,N). f(x,y) represents the gray value of each pixel (x,y).

N5 (b) N4 (c) N3 (d) N2 (f) N1

Figure 2. The tomato leaves characteristic image at 549 nm wavelength for four different nitrogen levels showing the different gradient of gray level.

Based on the variables obtained for the mean characteristic of tomato nitrogen hyperspectral image gray in different spectral bands, and the PLS method, the nitrogen detection model was established using the 25 samples from the total of 50 tomatoes:

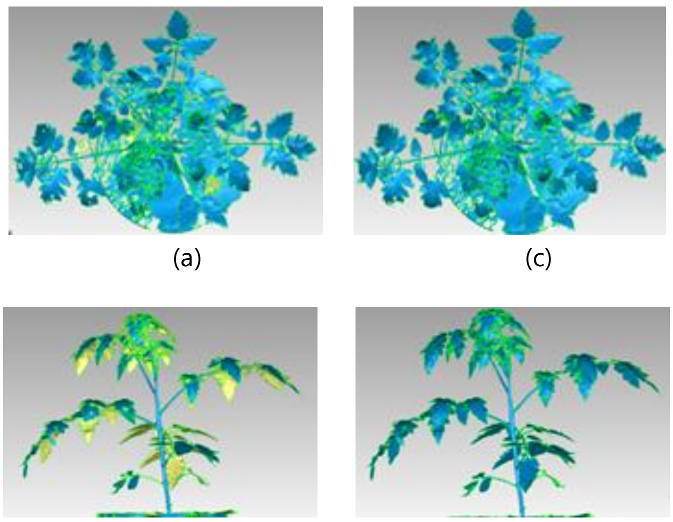
$$N = 1.75 + 7.81AG_{454} + 22.96AG_{549} - 27.21AG_{556} + 10.13AG_{663} \tag{6}$$

Using the remaining 25 samples for prediction analysis, the correlation coefficient of the model is 0.91 and the root mean square error is 0.66, which indicates that the hyperspectral image features can be used for detecting the tomato nitrogen with an improved accuracy.

Group form feature extraction and analysis of tomato nitrogen

3D scanning data preprocessing

In order to overcome the problems of noise produced by the reflection interference of objects around the sample, and the scan vulnerability during the 3D laser scanning the Geomagic qualify reverse engineering software was used to repair the model, and to obtain accurate scanning model. For the data repair, the Geomagic qualify software is needed to convert the tomato model which is composed of the triangle to the point cloud, to remove unwanted noise points. Then, transform the 3D point cloud to a surface model composed of triangles with encapsulation, to fill the holes existing on the surface of the tomato. Finally, the model of tomato was smoothed. Figure 3 (a) and (b) are the top view, the main view of the original three-dimensional data; figure 3 (c) and (d) are the data repaired. The repaired data effectively eliminated interference noise, and made the 3D data continuous.



(a) (c)

(b) (d)

Figure 3. The main view of the original three-dimensional data, (a) top view and (b) front view. The view for repaired data that effectively eliminated interference noise, and made the 3D data continuous, (c) repaired top view, and (d) repaired front view.

Group form feature extraction of tomato nitrogen

In this study, the volume, plant height and stem diameter of tomato were extracted by establishing spatial geometric model of point cloud data.

Volume calculation

Using a number of small cubes to fit the shape of tomato (Figure 4), the tomato region consists of cubes with the specification of a×a×a (the edge length of the cubes is less than the thickness of tomato leaves).

The volume of tomato was obtained by calculating the number of effective cubes. This algorithm does not need to consider the geometry of the tomato. What is required is just to determine the number and effectiveness of cube cells. In this case, the effective cube represents the physical portion of the tomato and the invalid cube represents the portion of the volume of the tomato. The formula for calculating the volume of tomato is given by:

$$S_k = aaM_i \tag{7}$$

$$V = \sum_{i=1}^{n} S_k = \sum_{i=1}^{n} aaM_i \tag{8}$$

where, V is tomato volume, Sk is the cross section area of tomato, a is cube side length, M is effective pixel grid.

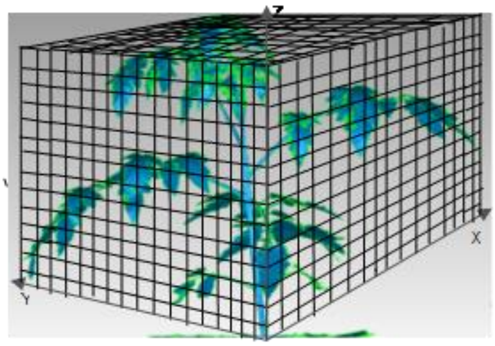


Figure 4. The cube for the tomato region obtained from the algorithm with specification of a×a×a, and showing that the edge length of the cubes is less than the thickness of tomato leaves.

Based on the measured value of the volume of tomato and the fresh weight of tomato, a model of biomass detection based on 3D scanning data was established as:

$$B_m = 1.07 + 0.93V \tag{9}$$

where, Bm is the biomass of tomato. The correlation coefficient of the model is 0.97 and the root mean square error is 0.32. The accurate retrieval of biomass characteristics can be realized by using the model obtained from tomato plants volume combined with biomass.

Plant height calculation

To determine the maximum value of Zmax and the minimum value of Zmin along Z-axis direction, the coordinates of point cloud data at any point of f(x, y, z), is required. Note that, at the maximum value of Zmax, the coordinates point is f(x1, y1, z1), and at the minimum value of Zmin, the coordinates point is f(x2, y2, z2). The plant height Ph can be obtained by calculating the distance between the two using the following formula:

$$P_h = Z_{\max} - Z_{\min} = Z_1 - Z_2 \tag{10}$$

Stem diameter calculation.

From the beginning at 4 cm from the bottom along the plant height direction, 3 tomato plant stem cross sections were intercepted at every 5 mm interval. The diameter of each cross section is calculated, and the tomato plant stem diameter was determined by the mean.

The tomato stem image comprises a layer of dots cloud. Finding out the maximum values and the minimum values along the X-axis and Y-axis respectively in the X-Y plane, as xmax, xmin, ymax and ymin, the diameter of this cross section can be calculated. Equation 11 was used for the stem diameter calculation as follows:

$$S_c = \sum_{i=1}^{3}[(x_{i\max} - x_{i\min})] + [(y_{i\max} - y_{i\min})]/6 \tag{11}$$

where, Sc is the tomato stem diameter; ximax and ximin are the maximum and minimum values in the X axis direction on the cross section images of the i layer (i=1,2,3); yimax and yimin are those values in the Y axis direction.

Based on the growth characteristics obtained for the nitrogen in tomato, the nitrogen detection model of tomato growth characteristics was established with 25 of the samples out of the total of 50 tomatoes:

$$N = 0.64 - 0.35S_c + 0.08P_h + 0.012B_m \tag{12}$$

Correlation coefficient of 0.92 and root mean square error of 0.79 were obtained for the model.The results show that the crop features can be used for the detection of tomato nitrogen. However, the nitrogen is just one of the several main factors that affect the crop growth. Therefore, it is difficult to achieve the ideal effect relying solely on single growth characteristics for nitrogen diagnosis.

Nitrogen multi-feature fusion model establishment

This study is based on the characteristics of hyperspectral images obtained from 454, 549, 556, and 663nm, as well as the growth characteristics of stem diameter, plant height and biomass. Using partial least squares regression (PLSR) [19] for information fusion, the tomato nitrogen multi-feature detection model was established. In order to overcome the scale differences between variables, equation (13) was used firstly to normalize the two different types of the characteristic variables:

$$x_i' = (x_i - x_{\min})/(y_{\max} - y_{\min}) \tag{13}$$

where, x is the characteristic value of the feature vector; i is the serial number (i=1,2,3...); xmax and xmin are the maximum and the minimum characteristic value of the samples in the feature vectors.

The partial least squares correlation analysis (PLS) was carried out by 4 image features and 3 long potential features using the data from 25 samples obtained simultaneously at the sample collection. The relationship between the components of PLS and the nitrogen content of the leaves was established and the PLS nitrogen regression model based on the original variable was obtained.

$$N = -4.15 + 8.23\mathrm{AG}_{454} + 15.36\mathrm{AG}_{549} + 27.91\mathrm{AG}_{556} \\ -31.85AG_{663} + 3.52S_c - 3.78P_h + 0.29B_m \tag{14}$$

While to validate the model by using the 25 samples; the correlation coefficient between the predicted value and the measured value was 0.94 and the root mean square error was 0.48. It shows that the prediction accuracy of the model is significantly improved by the fusion of hyperspectral images and growth features.

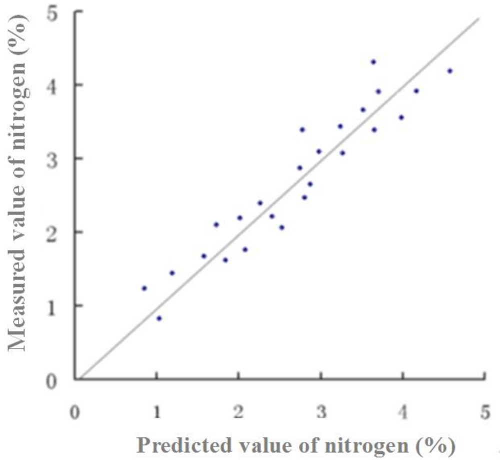


Figure 5. The chart for the correlation between the predicted values of nitrogen and chemical analysis measured values of nitrogen.

CONCLUSION

This study was aimed at quick and nondestructive detection of tomato nitrogen, based on the technology of hyperspectral imaging combined with 3D laser scanning. The nitrogen feature image and the response regularity of the tomato growth parameters at seedling stage under different nitrogen conditions were obtained. The characteristic wavelengths of tomato nitrogen of 454, 549, 556, 663nm were selected by the sensitive interval stepwise regression method and self-adaptive band selection method. The three-dimensional morphology of tomato was obtained based on the three-dimensional laser scanning technology. The spatial geometric model was built to extract the shape characteristic parameters such as stem diameter, plant height and biomass. A multi scale and multi-feature fusion detection model of nitrogen in tomato was established by PLSR method and the precision of the model R2 reached 0.94. The extracted features and selected models can provide a scientific basis for the environmental control which is based on the feedback of crop growth.

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References

[1] Deng, X.; Huang, J.; Rozelle, S.; Uchida, E. Cultivated land conversion and potential agricultural productivity in China, Land Use Policy, 2006, 23, 372–384

[2] Mueller, N.D.; Gerber, J.S.; Johnston, M.; Ray, D.K.; Ramankutty, N.; Foley, J.A. Closing yield gaps through nutrient and water management. Nature, 2012, 490, 254–257.

[3] Quemada, M.; Gabriel, J.L. Approaches for increasing nitrogen and water use efficiency simultaneously, Global Food Security, 2016, 9, 29–35

[4] Mikkelsen R.L. Tomato Flavor and Plant Nutrition: A Brief Review, Better Crops, 2005, 89(2), 14-15

[5] Kobryń, J.; Hallmann, E. The Effect of Nitrogen Fertilization on the Quality of Three Tomato Types Cultivated on Rockwool Acta Hort. 2005, 691, 341-348

[6] Taulavuori, K, Taulavuori E, Sheppard L.J. Truths or myths, fact or fiction, setting the record straight concerning nitrogen effects on levels of frost hardiness Environmental and Experimental Botany, 2014, 106, 132–137

[7] Dangler, J.M.; Locastio, S.J. External and internal blotchy ripening, and fruit elemental content of tricle-irrigated tomatoes as affected by N and K application time. J. Amer. Soc. Hort. Sci. 1990, 115, 547-549.

[8] Rodriguez, A.; Leoni, S.; Bussieres, P.; Dadomo, M.; Christou, M.; Macua, I.J.; Cornillon, P. The influence of water and nitrogen levels on the quality of the processing tomato grown in European Union countries. Acta Hort. 1994, 376, 275-278.

[9] Cossani, C.M.; Slafer, G.A.; Savin, R. Nitrogen and water use efficiencies of wheat and barley under a Mediterranean environment in Catalonia. Field Crop Res. 2012, 128, 109–118.

[10] Hao, Y.; Chen, B. Quantitative determination of low amino acid contents in tea by using near-infrared spectroscopy [J]. Transactions of the Chinese Society for Agricultural Machinery, 2014, 45(6), 216 - 220. (in Chinese)

[11] Rotbart, N.; Schmilovitch Z.; Cohen, Y.; Alchanatis V.; Erel, R.; Ignat, T.; Shenderey, C.; Dag, A.; Yermiyahu, U. Estimating olive leaf nitrogen concentration using visible and near-infrared spectral reflectance [J]. Bio systems Engineering, 2012, 114(2013), 426-434.

[12] Zhang, X.; Liu, F.; He, Y.; Gong, X. Detecting macronutrients content and distribution in oilseed rape leaves based on hyperspectral imaging [J]. Biosystems Engineering, 2013, 15(1): 56-65.

[13] Ramoelo. A.; Skidmore, A.; Schlerf, M.; Ignas H.; Renaud, M.; Azong, C.M. Savanna grass nitrogen to phosphorous ratio estimation using field spectroscopy and the potential for estimation with imaging spectroscopy [J]. Journal of Applied Earth Observation and Geo. Information. 2013, 23, 334 -343.

[14] Wang, S. Vegetable nutrition and quality [M] Beijing: Science Press, 2009: 36-37.

[15] Zhang, X.; Mao, H.P.; Zhou, Y. Detection based on water lettuce Leaf hyperspectral imaging technology of Anhui Agricultural Sciences, 2011, 39 (33), 20329-20331.

[16] Tony, B; Luo, X; Yang, B. AA3 Continuous Flow Analyzer (CFA) simultaneous determination of rubber leaf total nitrogen, study total phosphorus, total potassium method [J] Tropical, 2011, 32 (7): 1258 -1264.

[17] Su, J; Furong, H; Zhou, J. Statistical software SPSS for Windows Practical Guide [M] Beijing: Electronic Industry Press, 2000.

[18] Tong, Q. China Remote Sensing Spectral Characteristic Analysis [M] Beijing: Science Press, 1990.

[19] Shetty, N; Gislum, R. Quantification of frusta concentration in grasses using NIR spectroscopy and PLSR [J]. Field Crops Research, 2011, 120(1): 31-37.

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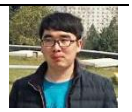
1st Author	Xue Wei Zhang	MSc student, Research interest: engaged in the research of nutritional information detection in crops. Email: 915349011@qq.com	
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